THE BIZARRE IMPACT OF COVID-19 PANDEMIC ON HOUSING PRICES ON OAHU ISLAND, HI

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**INTRODUCTION**

This paper investigates the impacts of COVID-19 pandemic on the housing market on Oahu Island, Hawaii. This ongoing pandemic crisis has brought a lot of fears and uncertainties to our society especially in the states with high death rates related to the virus. Comparing with other states, Hawaii has one of the lowest death rates in the United States. Even though Hawaii state has experienced far less spread than all the other US states, this pandemic affects this tourism-based economy, making business suffer, closing its schools and straining its healthcare system. On March 14, 2020, Hawaii found the first positive case in a Grand Princess passenger who had returned to Hawaii. Due to the increasing number of positive cases, Caldwell, the former mayor of Honolulu, announced stay-at-home orders beginning on March 23, 2020, lasting until April 30, 2020. For the first time, Hawaii Tourism Authority asked media to discourage people to travel to all the Hawaii islands. Hawaii’s former governor David Ige approved a second stay-at-home order from August 27 to September 24, 2020. Oahu has reopened on March 11, 2021. This paper evaluates how households value the current housing market during the COVID-19 pandemic, which affects the housing prices negatively, positively, or nothing? Hawaii is called paradise, the median housing price in Hawaii is above 1 million dollars. There is always a growing demand for houses in Hawaii, but will the COVID-19 affect people’s dreams of living in Hawaii and reduce their passions in buying properties from Oahu Island? The bizarre thing happened during the pandemic is that the housing prices increased dramatically on Oahu Island. The factors contributing to this bizarre increase in housing prices could be the historically low mortgage rates and the appealing of living in Hawaii state which seems so much safer than other states increase. Buyers might want to buy more houses due to the low mortgage rates, which make the cost of buying a house much cheaper. And the buyers might also want to buy a house to live in for health and safety purposes especially the Hawaii state is a much safer place to live in. In addition to the increased demand and limited supply, other factors might also have contributed to the unusual housing prices in Hawaii. For example, lumber prices have skyrocketed, having nearly tripled in price since 2020. The increasing demand from home renovation projects, new home constructions, Honolulu Rail Transit construction, and decreased global production might have contributed to the rising housing prices in Hawaii. This paper contributes to the literature by including the first island study including the spatial patterns and spatial heterogeneity of housing price changes in Hawaii’s single-family housing and condo markets during the COVID-19 pandemic crisis. As far as we know, there are no studies that investigate the impact of the COVID-19 pandemic on an island’s housing market. The goal of this study is to explore the impact of the COVID-19 pandemic on the housing prices on Oahu Island, HI.

**LITERATURE REVIEW**

The studies on the relationship between the COVID-19 pandemic and housing values can be grouped into three categories: studies that find no measurable effects on property values; studies that find negative impacts on property values, and studies that find mixed results from different study areas or different periods during the pandemic.

Bricongne, Meunier, and Pouget (2022) analyze a large database and find that the listing prices after the lockdown experienced a continued decline in London but increased in other regions. Yang et.al. (2023) analyze the association between to-metro and by-metro accessibility and house prices in Chengdu, China and find different impacts on low-priced houses and high-priced houses. Hu, Lee, and Zou (2021) find a negative relationship between prior COVID-19 cases and daily housing returns by examining five Australian capital cities. Wang (2021) investigate the effect of COVID-19 on house prices in Houston, Santa Clara, Honolulu, Irvine, and Des Moines. Wang concludes that only Honolulu experience noticeable house price declines from the outbreak, which is contrary to our findings. He also concludes that Santa Clara and Irvine lead the house price increase rates, followed by Des Moines and Houston. Cheung et.al. (2021) investigate the COVID-19 epicenter in China, and find the house prices fall immediately 4.8% by using hedonic pricing model and 5.0-7.0% by using price gradient model after the breakout. They also find that the house prices in the 62 areas in Wuhan City where the COVID-19 pandemic originated rebounded after the lockdown period, and price gradients were flattened from the epicenter to the urban peripherals. Li and Zhang (2021) conclude that the influence of the COVID-19 pandemic crisis on housing price change varied across space in the U.S. They also conclude that COVID-19 may make Americans more cautious about buying property in densely populated urban downtowns that had higher levels of virus infection.

**DATA and METHODOLOGY**

There are 10 variables associated with housing characteristics and 8 distance variables associated with amenities/disamenities. These distance variables are created using the ‘near’ function of ArcMap. The first step to assess the impact of the HRT on property values is to build a GIS database from the data collected from the Department of Planning and Permitting. Using sales data from the HBR (Honolulu Board of Realtors), more than 23,000 single family housing addresses and 33,000 condo addresses are geocoded. The housing data includes the major physical characteristics of the houses such as the number of bedrooms, bathrooms, square footage, age, etc. Hedonic analysis has been applied to data on heterogeneous goods to estimate shadow prices of bundled characteristics such as housing attributes and public good amenities acquired through the housing market (Ohsfeldt and Smith, 1985). Traditional hedonic estimation has been frequently used for the purpose of making inferences about non-observable values of different attributes like air quality, airport noise, and access to transportation (Espey and Lopez, 2000). There have been many critical views about traditional hedonic models such as information asymmetry, measurement validity of explanatory variables, market limitations, multicollinearity, and price changes. It is thus better to explore additional research designs or to use the hedonic price technique with application to other models.

Assuming P is a vector of house prices associated with a vector of structure variables S and set of location variables N then it follows that their relationship can be represented by the following model:

                                                (1)

where ln(Pi) = natural logarithm of house sale price of property i; Sip = physical attribute p of property i; Niq = location variable q of property i; β0, βp, βq= intercept and coefficients; εi= error. If the neighborhood feature affects house sale prices positively, the first-order relationship of house price with respect to the location variable is:

Shape

Description automatically generated with medium confidence                                                                               (2)

Table 1: Statistic Description of Single-Family Properties

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Description | Mean | StDev | Min | Max |
| Lnprice | Natural log of single-family housing prices | 11.92 | 0.467 | 11.92 | 16.79 |
| baths | The number of bathrooms | 2.37 | 0.98 | 0 | 17 |
| bedrooms | The number of bedrooms | 3.79 | 21.28 | 0 | 29 |
| Covid | 1 if there are positive covid cases | 0.407 | 0.491 | 0 | 1 |
| covidcases | Number of covid cases in each day | 28152 | 59695 | 0 | 249014 |
| urate | Unemployment rate without the percentage sign | 4.584 | 4.096 | 1.9 | 22.4 |
| age | The age of the house | 39.74 | 34.71 | 0 | 2017 |
| Age2 | The squares of the age of the house | 2784 | 52482 | 0 | 4068289 |
| Parking | The number of parking | 2.90 | 1.50 | 0 | 70 |
| lnsqft | The natural log of the square footage of the house | 7.53 | 0.437 | 5.39 | 10.06 |
| lnrail | The natural log of the distance to the nearest HRT station | 9.82 | 0.892 | 5.88 | 11.61 |
| lngolf | The natural log of the distance to the nearest golf course | 8.11 | 1.33 | 3.15 | 10.81 |
| lnpkschool | The natural log of the distance to the nearest preschool | 7.78 | 0.76 | 3.62 | 10.12 |
| lnprivate | The natural log of the distance to the nearest private school | 8.48 | 0.827 | 4.37 | 10.75 |
| lnpublic | The natural log of the distance to the nearest public school | 7.65 | 0.677 | 3.92 | 10.12 |
| lnhospital | The natural log of the distance to the nearest hospital | 9.44 | 0.885 | 4.44 | 11.14 |
| lnpark | The natural log of the distance to the nearest park | 6.93 | 0.152 | 2.93 | 9.38 |
| lnairport | The natural log of the distance to the nearest airport | 10.14 | 0.731 | 4.27 | 11.46 |
| bad | 1 if the house condition is bad | 0.028 | 0.166 | 0 | 1 |
| fair | 1 if the house condition is fair | 0.062 | 0.242 | 0 | 1 |
| average | 1 if the house condition is average | 0.184 | 0.387 | 0 | 1 |
| aaverage | 1 if the house condition is above average | 0.436 | 0.496 | 0 | 1 |
| excellent | 1 if the house condition is excellent | 0.289 | 0.453 | 0 | 1 |
| Y2016 | 1if the house was sold in the year of 2016 | 0.140 | 0.347 | 0 | 1 |
| Y2017 | 1 if the house was sold in the year of 2017 | 0.150 | 0.357 | 0 | 1 |
| Y2018 | 1 if the house was sold in the year of 2018 | 0.137 | 0.344 | 0 | 1 |
| Y2019 | 1 if the house was sold in the year of 2019 | 0.143 | 0.351 | 0 | 1 |
| Y2020 | 1 if the house was sold in the year of 2020 | 0.145 | 0.352 | 0 | 1 |
| Y2021 | 1 if the house was sold in the year of 2021 | 0.172 | 0.378 | 0 | 1 |
| Y2022 | 1 if the house was sold in the year of 2022 | 0.111 | 0.314 | 0 | 1 |

Table 2: Statistic Description of Condo Properties

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Description | Mean | StDev | Min | Max |
| Lnprice | Natural log of condo prices | 13.08 | 0.530 | 11.52 | 16.97 |
| baths | The number of bathrooms | 1.497 | 0.558 | 0 | 6 |
| bedrooms | The number of bedrooms | 1.798 | 0.913 | 0 | 8 |
| Covid | 1 if there are positive covid cases | 0.411 | 0.492 | 0 | 1 |
| covidcases | Number of covid cases in each day | 28152 | 59695 | 0 | 249014 |
| 0 | Unemployment rate without the percentage sign | 4.584 | 4.096 | 1.9 | 22.4 |
| age | The age of the house | 39.74 | 34.71 | 0 | 2017 |
| Age2 | The squares of the age of the house | 2784 | 52482 | 0 | 4068289 |
| Parking | The number of parking | 2.90 | 1.50 | 0 | 70 |
| lnsqft | The natural log of the square footage of the house | 7.53 | 0.437 | 5.39 | 10.06 |
| lnrail | The natural log of the distance to the nearest HRT station | 9.82 | 0.892 | 5.88 | 11.61 |
| lngolf | The natural log of the distance to the nearest golf course | 8.11 | 1.33 | 3.15 | 10.81 |
| lnpkschool | The natural log of the distance to the nearest preschool | 7.78 | 0.76 | 3.62 | 10.12 |
| lnprivate | The natural log of the distance to the nearest private school | 8.48 | 0.827 | 4.37 | 10.75 |
| lnpublic | The natural log of the distance to the nearest public school | 7.65 | 0.677 | 3.92 | 10.12 |
| lnhospital | The natural log of the distance to the nearest hospital | 9.44 | 0.885 | 4.44 | 11.14 |
| lnpark | The natural log of the distance to the nearest park | 6.93 | 0.152 | 2.93 | 9.38 |
| lnairport | The natural log of the distance to the nearest airport | 10.14 | 0.731 | 4.27 | 11.46 |
| bad | 1 if the house condition is bad | 0.028 | 0.166 | 0 | 1 |
| fair | 1 if the house condition is fair | 0.062 | 0.242 | 0 | 1 |
| average | 1 if the house condition is average | 0.184 | 0.387 | 0 | 1 |
| aaverage | 1 if the house condition is above average | 0.436 | 0.496 | 0 | 1 |
| excellent | 1 if the house condition is excellent | 0.289 | 0.453 | 0 | 1 |
| Y2016 | 1if the house was sold in the year of 2016 | 0.140 | 0.347 | 0 | 1 |
| Y2017 | 1 if the house was sold in the year of 2017 | 0.150 | 0.357 | 0 | 1 |
| Y2018 | 1 if the house was sold in the year of 2018 | 0.137 | 0.344 | 0 | 1 |
| Y2019 | 1 if the house was sold in the year of 2019 | 0.143 | 0.351 | 0 | 1 |
| Y2020 | 1 if the house was sold in the year of 2020 | 0.145 | 0.352 | 0 | 1 |
| Y2021 | 1 if the house was sold in the year of 2021 | 0.172 | 0.378 | 0 | 1 |
| Y2022 | 1 if the house was sold in the year of 2022 | 0.111 | 0.314 | 0 | 1 |

The hedonic pricing model was first proposed by Lancaster (1966) and later further expanded by Rosen (1974). This model might generate biased results, however, when the relationship between price and housing characteristics is not linear and in the presence of endogeneity. Additionally, the advantage of the hedonic pricing model is only realized in the presence of very reliable and detailed property records. Another issue is spatial dependence, which is derived from Tobler’s first law of geography (1970), “everything is related to everything else, but near things are more related than distant things” an axiom supported by Moran’s I test results indicating that there are strong spatial dependences existing in the house sales data for this study, in other words, there are significant spatial relationships between the houses’ locations and their property values. To address the omitted variable bias, this study uses fixed neighborhood effects model. Fixed effects model assumes that something within the same neighborhood may impact the house prices and those within-neighborhood effects have to be controlled. This model helps remove the effect of unobserved time-invariant or neighborhood-invariant variables from the regression process. The general fixed neighborhood effects model is constructed as follows:



where:

Ln(Pnt)is the housing price for the home located in the *nth* neighborhood in the tth year.

*Snt* is the structural variable for the home located in the *nth* neighborhood in the tth year.

*Lnt* is the location variable for the home located in the *nth* neighborhood in the tth year. is the error term that accounts for the variations between the same neighborhood and the same year.  represents all unobserved factors that vary across neighborhoods but are constant over time while represents all unobserved factors that vary both across the neighborhoods and the years.

 is the constant in the regressions.

To address the spatial dependence problems, this study uses semiparametric model to include geographical coordinates as its nonparametric part. The parametric models always assume strict functional forms, in which the dependent variable is determined by the regressors and unobserved errors are identically and independently distributed (iid). Nonparametric models, on the other hand, impose very few restrictions on the functional form leaving little room for misspecification. However, the precision of estimators which impose only nonparametric restrictions is poor (Powell, 1994) and there is a “curse of dimensionality”. Semiparametric models include the merits of both parametric and purely nonparametric models and is estimated in this study in the form:



where:

β = average coefficient of X.

Xi = a vector of structural and locational variables of for house i.

Zi1 = latitude of house i.

Zi2 = longitude of house i.

λ = error term.

m = purely nonparametric function.

The nonparametric part of the semiparametric model could be explained by the locally weighted regression (LWR) model or LOWESS (locally weighted scatterplot smoothing). It is a purely nonparametric procedure for fitting a regression surface to data through multivariate smoothing: the dependent variable is smoothed as a function of the independent variables in a moving fashion analogous to how a moving average is computed for a time series (Cleveland and Devlin, 1988). Detailed application of this model applying to housing market is found in McMillen and Redfern (2010): The LWR estimator is derived by minimizing the following equation with respect toand:



The kernel function K (*z*) determines the weight that each house sold as an observation in estimating the housing price at target point *X* with *Xi – X* defined as the distance between the target point and the *i*th neighboring house and *h* is a smoothing parameter called the bandwidth. As the distance increases, the weight declines; thus a kernel represents a decreasing function of a distance between two objects. There are various types of kernel functions such as rectangular, triangular, bisquare, tricube or Gaussian, however, the choice of kernel weight function usually has little effect on the results (this study uses the tricube kernel weighting function). The real challenge is the choice of *h* as it determines how rapidly the weights decline with distance.[[1]](#footnote-1) By placing less weight on more distant observations, high values of *h* imply local regressions that produce more smoothing than do smaller bandwidths (McMillen & Redfern, 2010). The choice of optimal bandwidth in this study is based on Silverman’s Rule of Thumb. Silverman (1998) proposes the rule-of-thumb bandwidth as , where is the sample standard deviation, v is the order of the kernel, andis a constant depending on the type of kernel used. Since this study uses the tri-cube kernel, according to Silverman, the constant is 3.15 when the kernel order is 2.

**RESULTS**

**Table 1 Model results with dependent variable: lnprice (N=23,620) for single-family housing market**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | OLS Model | | Fixed Effects Model   (51 groups) | |
| Variables | Coef. | Std. Err. | Coef. | Std. Err. |
| baths | 0.083\*\*\* | 0.003 | 0.068\*\*\* | 0.002 |
| bedrooms | -0.077\*\*\* | 0.002 | -0.049\*\*\* | 0.002 |
| Covid | 0.127\*\*\* | 0.018 | -0.100\*\*\* | 0.014 |
| Covidcases | 4.92e-07\*\*\* | 1.27e-07 | 4.46e-07\*\*\* | 1.01e-07 |
| urate | -0.007\*\*\* | 0.001 | -0.005\*\*\* | 0.001 |
| Age | 0.004\*\*\* | 0.000 | 0.0006\*\*\* | 0.000 |
| Age2 | -1.96e-06\*\*\* | 5.96e-08 | -2.62e-07\*\*\* | 5.16e-08 |
| parking | 0.005\*\*\* | 0.001 | 0.013\*\*\* | 0.001 |
| lnsqft | 0.663\*\*\* | 0.006 | 0.488\*\*\* | 0.017 |
| lnrail | 0.080\*\*\* | 0.003 | 0.073\*\*\* | 0.005 |
| lngolf | -0.006\*\*\* | 0.001 | 0.010\*\*\* | 0.001 |
| lnpkschool | 0.039\*\*\* | 0.003 | 0.026\*\*\* | 0.003 |
| lnprivate | -0.007\*\*\* | 0.003 | -0.039\*\*\* | 0.003 |
| lnpublic | 0.016\*\*\* | 0.003 | 0.026\*\*\* | 0.003 |
| lnhospital | -0.111\*\*\* | 0.003 | -0.009\*\*\* | 0.003 |
| lnpark | -0.026\*\*\* | 0.002 | -0.027\*\*\* | 0.005 |
| lnairport | 0.001\*\*\* | 0.004 | 0.041\*\*\* | 0.004 |
| bad | -0.100\*\*\* | 0.013 | omitted | omitted |
| fair | omitted | omitted | 0.091\*\* | 0.010 |
| average | 0.059\*\*\* | 0.008 | 0.151\*\*\* | 0.009 |
| aaverage | 0.112\*\*\* | 0.008 | 0.200\*\*\* | 0.009 |
| excellent | 0.193\*\*\* | 0.008 | -0.270\*\*\* | 0.009 |
| Y2016 | -0.065\*\*\* | 0.007 | -0.219\*\*\* | 0.022 |
| Y2017 | -0.323\*\*\* | 0.007 | -0.178\*\* | 0.022 |
| Y2018 | omitted | omitted | -0.144\*\*\* | 0.022 |
| Y2019 | -0.006 | 0.007 | -0.148\*\*\* | 0.022 |
| Y2020 | -0.012 | 0.001 | -0.149\*\*\* | 0.019 |
| Y2021 | 0.082\*\*\* | 0.017 | -0.037\*\*\* | 0.016 |
| Y2022 | 0.102\*\*\* | 0.027 | omitted | omitted |
| R-squared | 0.669 | | 0.595 | |

***Notes:*** *\*10% significance, \*\* 5% significance, \*\*\*1% significance*

**Table 2 Model results with dependent variable: lnprice (N=33,597) for condo market**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | OLS Model | | Fixed Effects Model   (53 groups) | |
| Variables | Coef. | Std. Err. | Coef. | Std. Err. |
| baths | 0.131\*\*\* | 0.004 | 0.050\*\*\* | 0.004 |
| bedrooms | -0.159\*\*\* | 0.003 | -0.051\*\*\* | 0.003 |
| Covid | 0.042\*\*\* | 0.016 | 0.041\*\*\* | 0.014 |
| Covidcases | 3.58e-07\*\*\* | 1.02e-07 | 3.26e-07\*\*\* | 0.83e-07 |
| urate | -0.005\*\*\* | 0.001 | -0.004\*\*\* | 0.001 |
| Age | -0.007\*\*\* | 0.000 | -0.009\*\*\* | 0.000 |
| Age2 | 3.84e-06\*\*\* | 8.30e-08 | 4.80e-06\*\*\* | 7.32e-08 |
| parking | -0.011\*\*\* | 0.001 | -0.003\*\*\* | 0.001 |
| lnsqft | 0.945\*\*\* | 0.007 | 0.826\*\*\* | 0.006 |
| lnrail | -0.072\*\*\* | 0.002 | -0.083\*\*\* | 0.003 |
| lngolf | 0.012\*\*\* | 0.001 | -0.007\*\*\* | 0.001 |
| lnpkschool | 0.010\*\*\* | 0.002 | 0.004\*\*\* | 0.002 |
| lnprivate | 0.027\*\*\* | 0.003 | 0.025\*\*\* | 0.003 |
| lnpublic | 0.016\*\*\* | 0.003 | 0.082\*\*\* | 0.003 |
| lnhospital | -0.067\*\*\* | 0.003 | 0.012\*\*\* | 0.003 |
| lnpark | -0.090\*\*\* | 0.002 | -0.065\*\*\* | 0.002 |
| lnairport | 0.095\*\*\* | 0.003 | 0.142\*\*\* | 0.004 |
| bad | -0.096\*\*\* | 0.026 | -0.109\*\*\* | 0.022 |
| fair | omitted | omitted | omitted | omitted |
| average | 0.110\*\*\* | 0.011 | 0.090\*\*\* | 0.009 |
| aaverage | 0.178\*\*\* | 0.010 | 0.151\*\*\* | 0.009 |
| excellent | 0.283\*\*\* | 0.011 | 0.225\*\*\* | 0.009 |
| Y2016 | -0.266\*\*\* | 0.016 | -0.272\*\*\* | 0.014 |
| Y2017 | -0.210\*\*\* | 0.016 | -0.216\*\* | 0.014 |
| Y2018 | -0.168\*\*\* | 0.016 | -0.168\*\*\* | 0.014 |
| Y2019 | -0.163\*\*\* | 0.016 | -0.162\*\*\* | 0.014 |
| Y2020 | -0.169\*\*\* | 0.011 | -0.167\*\*\* | 0.009 |
| Y2021 | -0.101\*\*\* | 0.006 | -0.106\*\*\* | 0.005 |
| Y2022 | omitted | omitted | omitted | omitted |
| R-squared | 0.722 | | 0.595 | |

**CONCLUSIONS**

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1. The tricube kernel is structured as D(t) =(1-|t|3)3*I*(|t|≤1) and 0 otherwise. [↑](#footnote-ref-1)